Load demand profile for a large charging station of a fleet of all-electric plug-in buses

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Abstract: This study proposes a general procedure to compute the load demand profile from a parking lot where a fleet of buses with electric propulsion mechanisms are charged. Such procedure is divided in three different stages, the first one models the daily energy utilisation of the batteries based on Monte Carlo simulations and route characteristics. The second one models the process in the charging station based on discrete event simulation of queues of buses served by a lot of available chargers. The third step computes the final demand profile in the parking lot because of the charging process based on the power consumption of batteries' chargers and the utilisation of the available charges. The proposed procedure allows the computation of the number of required batteries' chargers to be installed in a charging station placed at a parking lot in order to satisfy and ensure the operation of the fleet, the computation of the power demand profile and the peak load and the computation of the general characteristics of electrical infrastructure to supply the power to the station.

1 Introduction

Public transportation of passengers by means of urban buses is very popular around the world, and these buses operate on transit lines or routes. Each route is characterised by a line length, pre-defined passenger stops and it can follow a circular route or single track lines [1]. Currently, the majority of buses use gasoline or diesel as combustible fuel. The new advances of electric buses have allowed the utilisation of all-electric buses (or pure electric buses), which are an alternative to traditional buses because they are shown to be an effective way to save energy, reduce CO_2 emissions [2]. However, the industrialisation process of pure electric buses must be accompanied by the development of an electrical infrastructure for the electrification of this transportation system.

Currently, there are different battery recharging systems applied to buses; such as plug-in recharging station, induction recharging and on route charging station. In the first case, depending of the storage capacity of batteries, the electrification of the transportation system requires designation of certain bus stops for recharging [3] in single track lines or it is required to recharge the batteries of the buses one or several times by day at the parking lot for circular routes, for example.

The number of times that a battery requires recharging in a period of time depends on the utilisation characteristics of buses, such as: the length of the route, drive cycle and the characteristics of the on-board energy storage capacity [4, 5]. On the other hand, a fleet of urban public buses can share the electrical infrastructure to recharge the batteries according to the routes, service zones, and other factors. The way the recharging system is used goes to determine the power requirements that are demanded from the distribution power system, and the infrastructure required for the connection to it.

Therefore, this paper proposes a model to compute the load demand profile from a parking lot where a fleet of buses with electric propulsion mechanisms are charged. Such model is divided into three different stages in order to represent the energy utilisation of the batteries, model the process in the charging station and compute the final demand profile in the parking lot because of the charging process. The energy utilisation by each bus allows the computation of the state of charge (SOC) of the battery. Hence, this paper proposes to develop Monte Carlo sequential simulations that make use of some deterministic parameters (for example, length of the route) and probabilistic

parameters (for example, the initial SOC for each bus). The recharging process must prepare the fleet of buses for appropriate operation; so, it is required to use a recharging station that provides the energy to the batteries. This paper proposes use of discrete events simulations in order to represent the service of charging of a queue of buses to store energy (increase SOC) before starting the daily operation of each bus, and that are served by a lot of available chargers in a parking lot. Finally, based on the power consumption of batteries' chargers and the utilisation of the available charges, the power load demand profile is computed. Section 2 of this paper explains in detail the proposed model.

Section 3 presents the application of the model for a fleet of 60 buses that serve an urban zone by means of ten circular routes. It is assumed to be a fleet of all-electric buses with a charging system of 100 kW at 480 V. Finally, Section 4 presents the conclusions of this paper.

2 General three-stage model

The purpose of the general procedure, here proposed, is to compute the load demand profile that is obtained at the parking lot when the batteries of a fleet of all-electric buses are charged. This procedure is divided in three main stages as shown in Fig. 1. The first step consists of modelling the energy utilisation of the batteries for the complete fleet of buses, represented by the computation of the SOC. Then, assuming that all buses are charged at a large charging station (a parking lot with many connection points for battery recharging) and, also, a lower number of charging points than buses, a model of utilisation of the charging points based on simulation of discrete events is proposed. Finally, the way as each bus's connection point is used is interpreted in power demand consumption.

2.1 Modelling the SOC of a fleet of buses

The first important step in this procedure is to establish the SOC of each one of the buses related to the parking lot. This computation involves modelling the energy consumed by such buses, in one day period, because of the different routes followed by them.

Let us assume that in a parking lot there are associated N buses that use it as night parking in non-service schedule and recharge batteries at that place. These N buses provide the service to M
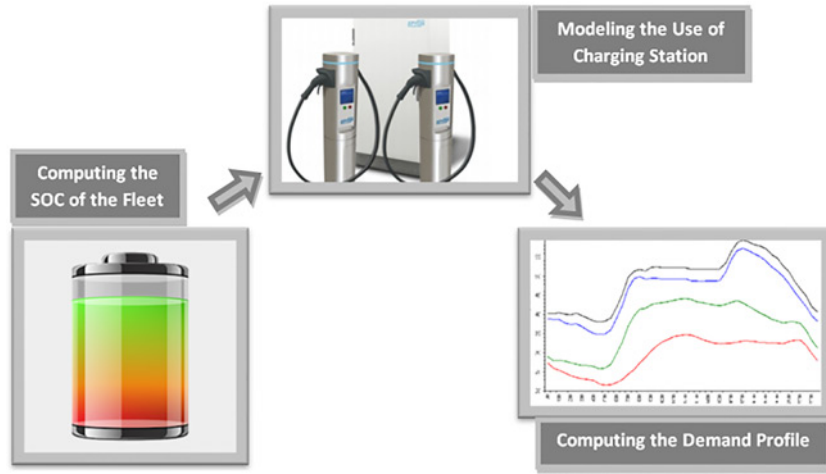
Fig. 1 *General scheme of the three-stage model*

circular routes during the day; each route (j) has a length L_j and a schedule of opening (T_{oj}) and closing (T_{cj}) times. On one hand, the buses could be assigned to each route by a daily schedule that takes into account a departure frequency (f_t) from the main stop and the time spent in each route (ΔT_j). Alternatively, the buses can be assigned to each route based on a first in-first out logic where each one of the buses that finishes its travel on a route will enter to the last place of the queue and wait the route assignation based on a local dispatcher. Therefore, in this case, a bus can make different routes several times during the day.

As a consequence, the daily energy consumption of each bus (i) is given by

$$\mathrm{EC}_i = \sum_{j=1}^{N_i} \left\{ \mathrm{CR}(j,\ t) \times L_j + \mathrm{SC} \times \Delta T_j \right\} \qquad (1)$$

where $\mathrm{CR}(j, t)$ is the energy consumption rate (CR) for each route j for a period t of the day (peak hours, valley or low-demand hours, night hours and other required class of time of day), N_i is the number of routes made by the bus i in the day, SC is the static consumption which refers to the energy consumed by the additional equipment of the bus (radio, lighting and air conditioning) and ΔT_j is the time spent in route by the bus.

Therefore, as shown in (1), the computation of EC_i requires knowing the N_i routes made by the bus i in the day. Thus, a sequential simulation of the operation of the N buses associated to the parking lot must be made, taking into account some deterministic parameters and other random variables. As scheduled parameters, the opening (T_{oj}) and closing (T_{cj}) times of route j, the starting time for bus i (T_{oi}), and the required dispatching frequency of buses according to the kind of hour of the day for each route (f_{tj}), that is, peak or valley hours are considered.
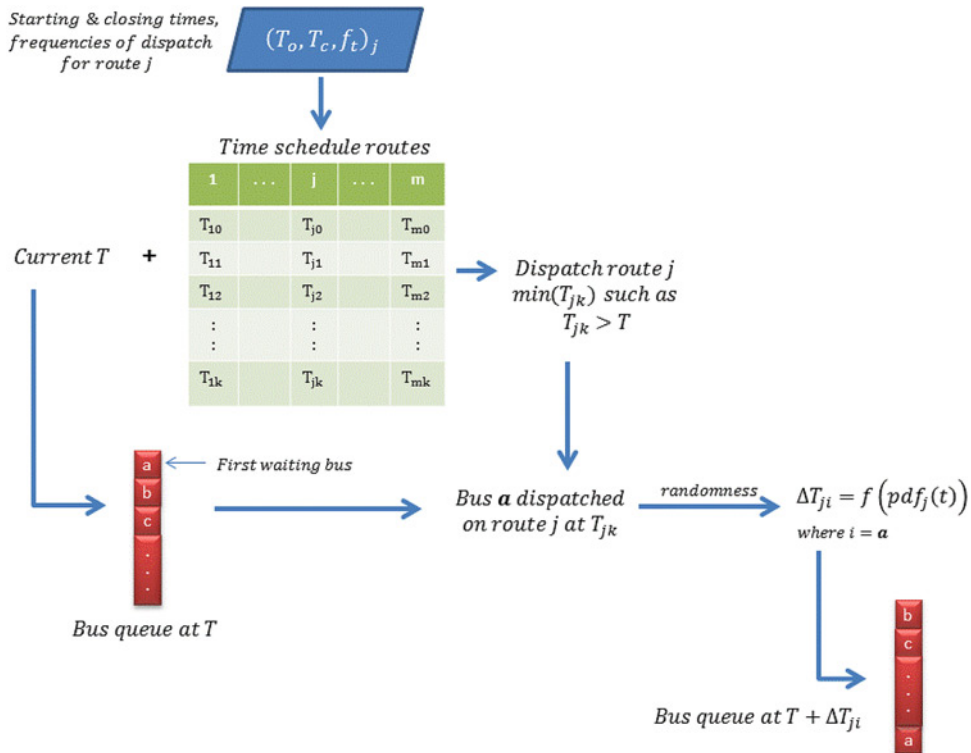

Fig. 2 *Scheme of dispatching buses by queue and random time for route service*

In contrast, the time (ΔT_{ji}) spent in the route j by the bus i, is modelled as a random variable based on the probabilistic distribution function ($\text{pdf}_j(t)$) that represents its random characteristics. This $\text{pdf}_j(t)$ depends on the period t of the day (peak hours, valley hours). These 'pdf' can be statistically adjusted from field studies of the time spent by current buses that make use of gasoline or diesel in the existing routes.

Hence, the proposed sequential simulation consists of a Monte Carlo simulation that uses N buses and M routes. At any time T, it is assumed that at the dispatching stop there is a queue of buses. The first bus in the queue is dispatched for serving the next route that requires a bus. Therefore, Fig. 2 shows that at T the first bus in the queue is 'bus a' and it is dispatched at T_{jk}, that is the next time for departing any bus ($T_{jk} > T$). Then, based on the $\text{pdf}_j(t)$ for route j at the time period t (peak or valley hour), the time spent by 'bus a' on route j will be randomly generated and equal to ΔT_{ji}. Therefore at $T + \Delta T_{ji}$ the 'bus a' arrives at the bus queue and waits for despatching.

The simulation is made sequentially for the N buses and M routes for guaranteeing the representation of the operation of the service of the system. Naturally, this procedure could be modified according to other particular schemes of operation of the buses' system.

The other random characteristic included in the model is the SOC level at the beginning of the day for each bus i (for the first service on the day). Currently, there are buses with enough autonomy for moving, requiring only one battery recharge by day or several days. Therefore it would be possible that some of the buses do not require recharging one night at the parking lot because its SOC is enough for working the next day (more than 250 km [6]), that is, the forecasted EC_i is lower than the SOC of bus i at the beginning of the day. Then, this initial SOC could be included in the Monte Carlo simulation as a random variable between the minimum required SOC ($\min(SOC)$) for a complete working day and the maximum SOC level obtained at the fast battery charging process (around 80% of total storage capacity).

Finally, when the whole day simulation is done, the final value of SOC for each bus i is computed, stored and the one day simulation starts again until the number of Monte Carlo simulations is accomplished. At the end of the simulation, the statistical values of the SOC are obtained for each one of the buses. In this way, statistical characteristics of SOC level for buses is computed and used in the second step, the use of charging station, as explained in Section 2.3. Section 2.2 explains in detail the computation of the CR used in (1).

2.2   Computation of the CR

To estimate the energy utilisation of batteries, it is proposed to use a longitudinal dynamics model which will provide an approach to the power consumption behaviour of a feeder bus along a specific driving pattern. In general, these driving patterns are compiled in a driving cycle corresponding to a velocity profile, including the traffic characteristics of the studied city and its topography.

This case study starts from a simple dynamics model composed of some assumptions. These assumptions are in principle related to the driving patterns, such as the road is considered to be fully paved and flat. At the first stage, it is assumed the vehicle is going to follow a standard driving cycle; complementary accessories (i.e. air conditioning and additional electric devices) will not be taken into account, and regenerative braking will not be present.

Regarding the simulation phase, it is necessary to establish some simulation parameters beside the standard driving cycle characteristics. These parameters are those corresponding to the dynamic model characteristics. This model consists of resistive forces and inertial effects [7, 8] as shown in (2)

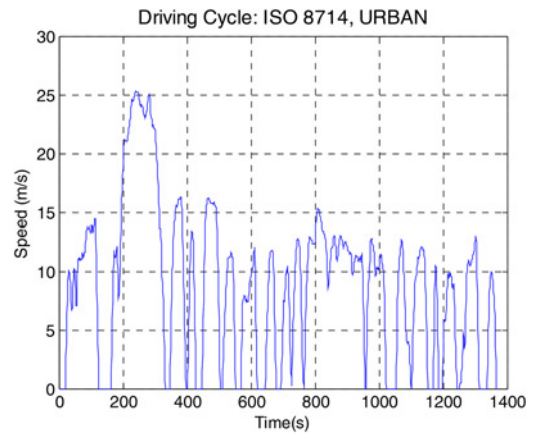$$\eta F_{\text{trac}} = F_{\text{aero}} + F_{\text{rr}} + F_{\text{g}} + Ma \qquad (2)$$

Fig. 3 *Velocity profile used in first-stage simulations*

These resistive forces are: aerodynamic force (F_{aero}), rolling force (F_{rr}) and gravitational force (F_{g}). The air density and the vehicle characteristics related to the aerodynamic drag are involved in the aerodynamic force; road conditions are involved in rolling resistance; altitude corresponding to the city topography is involved in gravitational force (at the first stage, this altitude is assumed to be zero); and characteristics inherent to the vehicle such as mass and efficiency of the power train are also involved in this model.

The driving cycle used in this stage of the simulation is the urban driving cycle corresponding to transit in USA included in the International Standard [9]. The velocity profile to follow in this standard is the one presented in Fig. 3.

Once the simulation parameters are established (i.e. including the vehicle main characteristics as weight, gross vehicle weight rating (GVWR), width, height and Cd), it is needed to explain how the batteries' SOC is going to be estimated for the scenarios of maximum weight operation and minimum weight operation (i.e. no passengers and no cargo). From driving conditions, given by the usage of the vehicle and the dynamics model implementation, the SOC will be delivered in accordance to an initial SOC.

Explaining further the dynamics model, first it is important to mention that it will be divided in traction case related to (2) and braking case, as follows

$$F_{\text{brk}} = -Ma - F_{\text{aero}} - F_{\text{g}} \qquad (3)$$

From this model, specifically from traction and braking forces, the energy stored in batteries will be estimated. Power and energy definitions will be determinant for it

$$E = \int P \, dt \qquad (4)$$

$$P = F.v \qquad (5)$$

This energy obtained from the period of a driving cycle will be the energy to store in batteries and, particularly, it will be its SOC based on an initial state, corresponding to the use of charging stations.

Implementing the standard urban driving cycle, the bus characteristics and the Bogota air density on the dynamics model, the power consumption and its sources are going to be determined for each scenario, and the respective energy consumption along the cycle.

2.3   Modelling the use of charging stations

The first stage of the proposed model obtains the SOC and arriving times at the end of the daily operation of each bus i at the parking station. As it was stated, at the end of the day, the bus i could have an SOC larger than that required to complete one day of job ('the
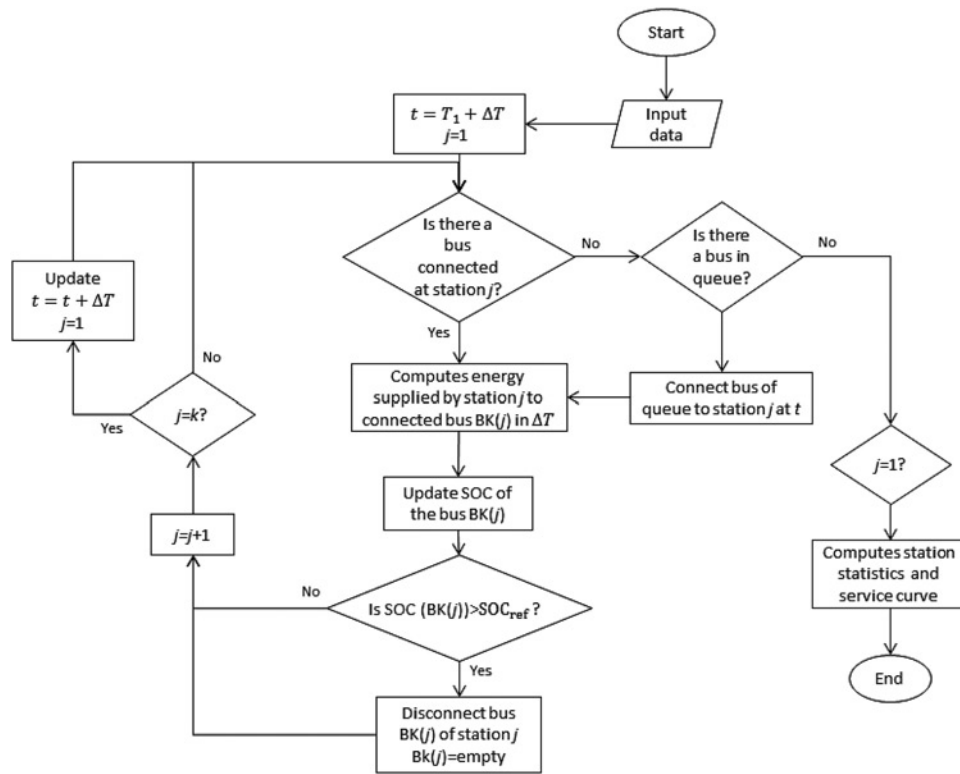
Fig. 4 *Algorithm for computing battery recharging service*

next day'), defined here as min(SOC), and in this case it is not required to recharge the batteries of the bus. By contrast, if the SOC is lower than min(SOC) then the batteries must be recharged. Thus

$$
\begin{aligned}
&\text{if } SOC_i \leq \min(SOC) \\
&\Rightarrow \text{bus } i \text{ makes the queue of recharge} \\
&\text{if } SOC_i > \min(SOC) \\
&\Rightarrow \text{bus } i \text{ is parked for operation 'next day'}
\end{aligned}
\tag{6}
$$

In consequence, a subset N_r of the N buses associated to the parking station requires to recharge batteries. The definition of min(SOC) should be based on previous calculation or simulations of the energy consumption of each bus and the energy needed to ensure the next day operation (using the stage 1 of this proposed model, Section 2.1).

On the other hand, these N_r buses will be served by a number of K fast charger stations placed at the parking station. The battery of each bus i is charged to a pre-established final SOC (for example, 80% or larger) in order to profit the larger slope of the characteristic of fast charging, as shown in Fig. 4. This value is not necessarily 100% and its definition could be based on the time of operation and characteristics of the charging device. After recharging the battery, bus i is parked in its place at the parking station.

One of the objectives of the K stations is to recharge all the N_r buses during the night before each bus starts its daily job. Therefore, based on the utilisation of these K stations by the buses, and the characteristic curves of the batteries charging process, the load demand profile can be built.

Hence, this paper proposes to model the utilisation of the K stations using a model of simulation of discrete events dynamic systems [10, 11].

Fig. 4 presents the algorithm for computing the battery recharging process. As input data, it is supplied with the results of the first stage of the proposed model (presented at Section 2.1),

where for the N_r buses requiring battery recharging, the SOC_i and the arrival time T_i of each bus i to the parking charging stations are known; as shown in Table 1.

The simulation is developed using a discrete time simulation step (ΔT) that satisfies

$$
\Delta T \ll T_{r,i} \quad \forall i = 1 \text{ to } N_r
\tag{7}
$$

where $T_{r,i}$ is the recharging time for bus i.

As Fig. 4 shows, for each ΔT, if a bus is connected at a charger station, the energy supplied in ΔT is computed and the SOC is updated for the connected bus at the station j (for $j = 1$ to K). As previously mentioned, the bus is disconnected when the pre-established final SOC (SOC_{ref}) is reached.

If at any time t a charger station is empty then the first bus placed in the queue is connected to the empty charger station. Finally, the simulation runs until the bus queue is empty and there is no bus connected at any charger station.

Hence, at the end of this second stage of the proposed model, each bus i has an SOC_i larger than SOC_{ref}. At the same time, the sequence of buses connected to each charger station and the duration of connection of buses served by each station is obtained.

Therefore the SOC_i for each bus i is employed for the 'next day' simulation using the procedure presented as the first stage of this proposed model (Section 2.1). On the other hand, the sequence

Table 1 Input data for discrete event dynamics simulation

Bus consecutive	SOC_i	Arrival time, h:min
1	SOC_1	T_1
2	SOC_2	T_2
⋮	⋮	⋮
N_r	SOC_{Nr}	T_{Nr}

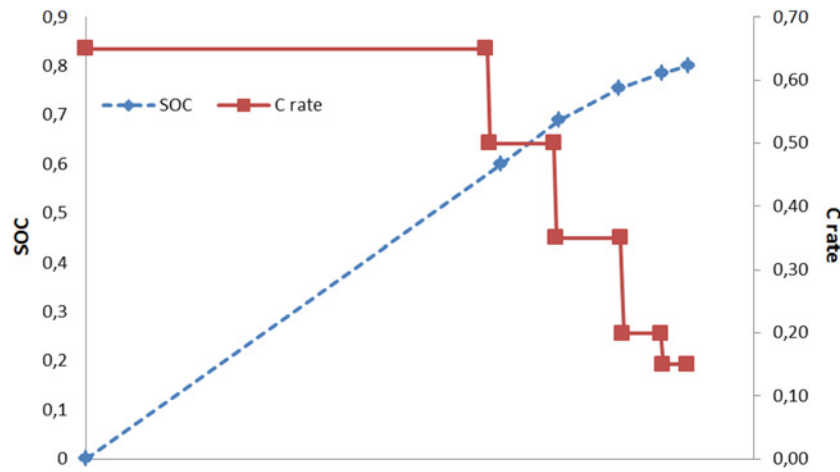Note: $T_{Nr} > \cdots > T_2 > T_1$.

Fig. 5 *Characteristic curves for fast batteries charging*

and durations of connected bus is used in the next stage for computing the load demand profile.

2.4 Computation of the charging time

There are different charging algorithms for batteries for electric vehicles [12]. The most common method consists of two modes, of operation according to the SOC of the battery. The first mode corresponds to a constant current (CC) mode and the second one to the constant voltage (CV) mode. During the first mode, the batteries demand the maximum current until the cells achieve nominal voltage [12]. In the CV mode, the fast charging requires reduced charging current.

The fast charging of batteries means that the charging is made at a high current rate (C-rate) [13]. In addition, different charging methods for optimal-charging patterns have been developed; such the multistage charging method [12–14].

In the multistage charging method, the battery is charged at CC until the nominal voltage is achieved. At this moment the process switches to the next current stage, of lower CC level than the previous [12–14]. Therefore, as Fig. 5 shows, a pattern of five-step CC could be employed for distributing the complete charging time [14, 15].

The decrease in the charge current should be slowest in each time step. In the five-step CC mode, the first high charge rate is the longest and the latest lowest charge rate is the shortest; in between this, there are three charging rates that take an even time. General process for a fast charge is shown in Fig. 5 [12–14]. There are several ways to obtain an idea of the power demanded by the battery in its charging process. However, dividing the power delivered by the charger into five sections would be a good approximation of this curve.

Therefore, from Fig. 5, the charging time for the bus *i* is computed as function of its SOC_i and the SOC_{ref}; thus

$$\Delta T_i = t(SOC_{ref}) - t(SOC_i) \qquad (8)$$

where $t(SOC_x)$ is the time required to recharge from 0 to the level SOC_x.

2.5 Computing the power demand profile

The third stage of the proposed model is the computation of the power demand profile of the parking station. As mentioned previously, the second stage of the model computes the sequence of utilisation of each fast battery charger.

At the same time, the second stage of the model has computed the change of the SOC of each bus *i* connected at the charger

station *j* between *t* and *t* + Δ*t*, according to Fig. 4. Thus, based on the charging characteristic curves of the charger station, the energy supplied by the charger *j* to the bus *I* during Δ*t* is computed. In this way, the average power of charging during the step of simulation Δ*t* is given by

$$P_j(t, \ t + \Delta t) = \frac{E_j(t, \ t + \Delta t)}{\Delta t} \qquad (9)$$

where $P_j(t, t + \Delta t)$ is the power consumption (load) of station *j* by charging the battery of the connected bus, during the interval *t* to *t* + Δ*t*.

Finally, the total demand of the parking lot with *k* charging stations is computed by aggregation of the individual loads of each charger for each instant *t*.

It is important to mention that the shorter the duration of the simulation step (Δ*t*), the better the results of the computation of the instantaneous load; however, the computing time will be longer.

3 Testing case

The bus rapid transit (BRT) consists of bus convoys, double-articulated buses, and has become a popular transportation system in many countries, especially in Latin America; for example, it had been implemented in the following cities: Curitiba (Brazil), Bogota, Cali, Barranquilla (Colombia), Santiago (Chile), among others [1]. Currently, these systems use diesel bi-articulated buses, exclusive ways and a complementary system of common buses that transport customers from neighbourhoods to the main exclusive way where are placed the BRT bi-articulated buses. This complementary system is known as 'Feeder Buses'.

The bi-articulated buses go along large paths from one gate to another gate. Associated with each gate, there are parking lots where the feeder buses are stored at night. At the same time, each gate is the departure point of feeder buses to the gate's neighbourhoods, using approximately 8–10 short bus paths.

Therefore this paper assumes the possibility to employ all-electric buses for the 'Feeder Buses' in order to develop a model that can be used to determine the power demand profile of a parking lot with a large charging station for these buses.

In this paper, it is assumed a fleet of all-electric buses with a charging system of 100 kW at 480 V where the status of charge (SOC) of the battery charges to the threshold given by the behaviour of the chargers [6]. In addition, it is assumed a parking lot of lower number of charging points than buses, such that several buses are charged by a queue.

As a test case, we take a parking lot of a fleet of all-electric buses that is placed near to one gate of a BRT system, based on public

Table 2 Data for the test case – fleet of all-electric buses

Parameters	Values
BRT's gate name	B
number of feeder paths (i.e. short bus paths)	10
number of feeder buses	60

Table 3 Data for the feeder paths

Path #	Length, km	Parameters for peak hours		Parameters for valley hours	
		Mean time, min	Time deviation, min	Mean time, min	Time deviation, min
1	7.36	32	5	28	5
2	3.93	45	5	41	5
3	5.85	35	8	30	8
4	8.42	30	7	27	7
5	6.80	30	3	26	3
6	2.90	20	7	15	7
7	4.28	30	5	27	5
8	5.48	28	6	24	6
9	5.82	30	5	25	5
10	3.51	20	5	14	5

average data of the Transmilenio BRT system of Bogota [16]. Therefore, Tables 2 and 3 present the parameters taken into account in the simulation.

It is important to have in mind that not all the feeder paths have the same hours of operation in the day. In this case, nine of them operate during the entire day from 5 am to 12 am; whereas path# 8 is only available in peak hours from 6 am to 9 am and 4 pm to 8 pm.

The test case comprises ten different neighbourhood paths departing from a common gate, as shown in Fig. 6. Besides the length and duration parameters, it is important to determine a CR for each one of the paths taking into account their different conditions, as explained in Section 2.2. On the other hand, in this case it is assumed an identical fleet of buses, so it is important to define the charging behaviour because of the characteristics of the corresponding batteries. Additionally, the energy consumption per kilometre is defined for each path using some measurements and statistical analysis of the performance of each bus in the path.
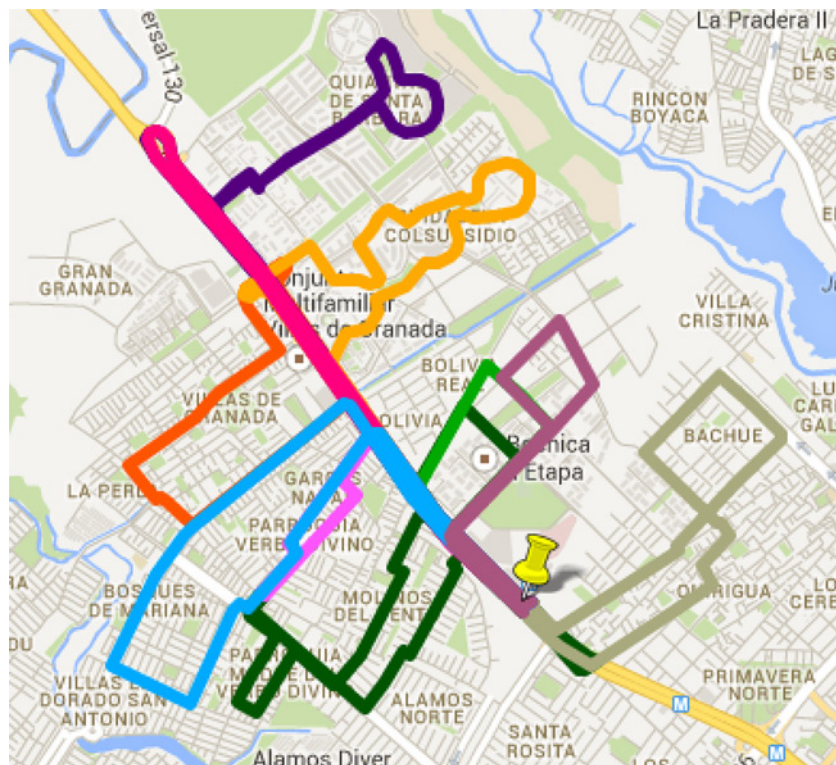
As a first approach to the problem, a Monte Carlo simulation was carried out in order to establish the average consumption of a bus in one day period. Initially, a uniform distribution was assumed for the initial status of the SOC for computing the daily consumption. For this case, the result was that an average 30% of the SOC was consumed in one day operation of the bus.

With the knowledge of this average consumption, the lower threshold of the charging policy is specified as 35% of the SOC. The upper threshold used was 82.5%, considering that after this value the charging process would be very slow and it would not be practical to plug in the whole fleet.

Particularly, in the case of a BYD k9 bus, a fast charge would equate to a delivery of 267.3 kWh, taking into account that its entire capacity is 324 kWh and that a fast charge would mean an upper threshold of 82.5% of the SOC [6].

This can be seen in Fig. 7, where the power demanded and the SOC for the BYD K9 in its charging process are shown. The additional values used as an input in the simulation are shown in Table 4. It is important to clarify that the number of chargers was a parameter changed in each simulation trial until the expected behaviour of the system was achieved.

After the model has finished its first stage, computing the arrival times and SOC of batteries at the end of the day, it is important to generate some histograms for these two parameters which will give

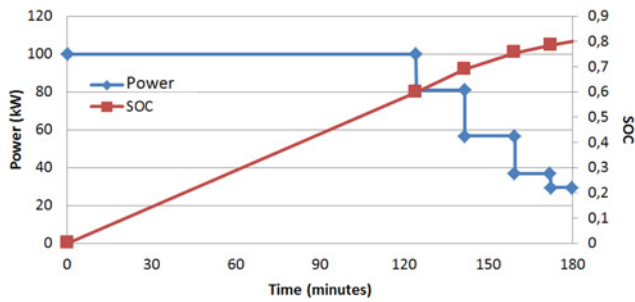**Fig. 6** Geographical paths of 'Feeder Buses'

Fig. 7 *Approximation of the charging process in five sections, BYD k9*

Table 4 Additional inputs for the model

Parameters	Values
frequency of departure in peak hours	10
frequency of departure in valley hours	20
frequency of departure in late-night hours	30
# of Monte Carlo simulations	1000
lower threshold of SOC (min(SOC))	35%
upper threshold of SOC (SOCref)	82.5%
number of chargers	10

a little bit more of understanding about the behaviour of the fleet and the energy consumed by each bus.

The histogram in Fig. 8 shows that there is a very narrow frame of time in which the buses are arriving to the parking station with inter-arrival times of a few minutes. On the other side, the histogram in Fig. 9 shows the number of vehicles with certain ranges of SOCs. Therefore, according to this histogram and the lower threshold of the charging policy, there are 27 buses on average that should be charged at the end of the day. Both histograms were calculated from the average results after all Monte Carlo simulations were completed.

The aggregated curve of power demand will begin with a demand equal to the entire capacity of the grouped chargers and then will start entering one by one as a queue with different SOCs. The aggregated power demand curve is shown in Fig. 10, with a time frame from 10 pm to 6 am. It could be reasonable that buses should be charged before the operation of the service starts, and that is 5 am in this case. However, not all the buses are going to start operation at 5am, some of them will start even an hour later, taking into account that the number of paths is smaller than the number of buses. The total energy consumed in the charging period was 3768 kWh.
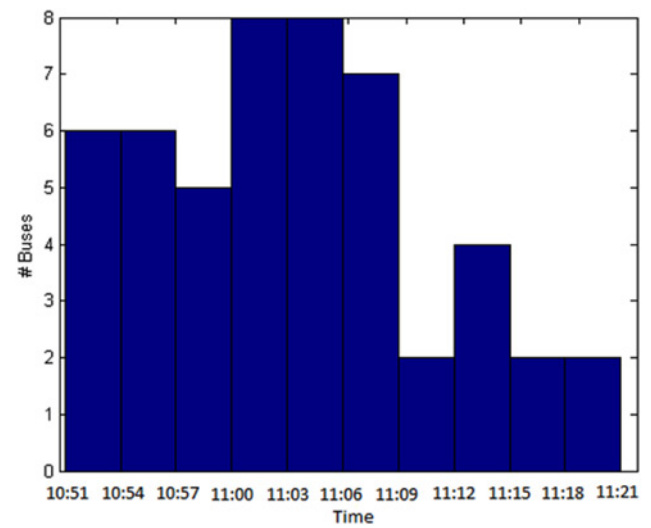

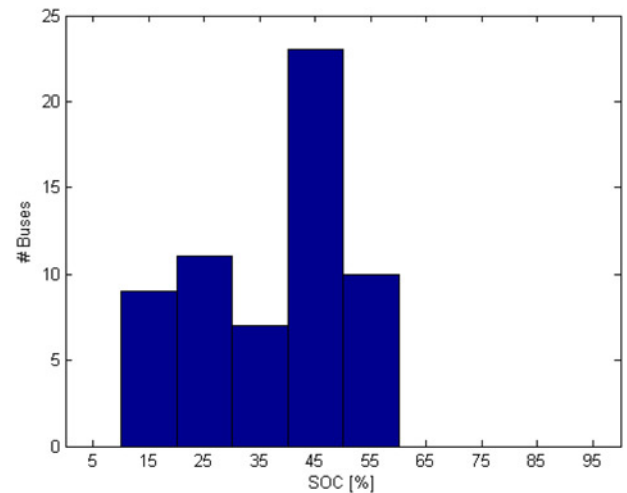**Fig. 8** *Histogram of arrival times of buses to the parking station*

Fig. 9 *Histogram of SOCs of buses at the end of the day*

This result gives us the number of chargers that will be needed to ensure the correct operation of the feeder service for the specific gate, which in this case would be ten chargers. However, considering possible contingencies up to $N - 1$, it would be better to have at least 11 chargers attending to the charging station. This can also be useful to give the dimension of the transformer needed to attend to
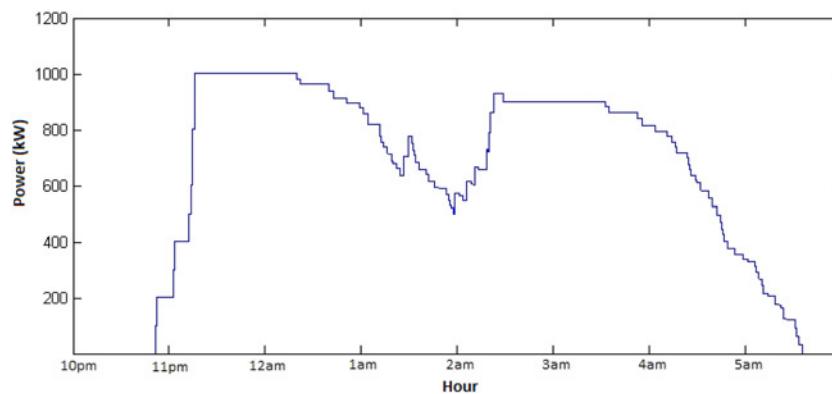

Fig. 10 *Aggregated power demand curve of the charging process*
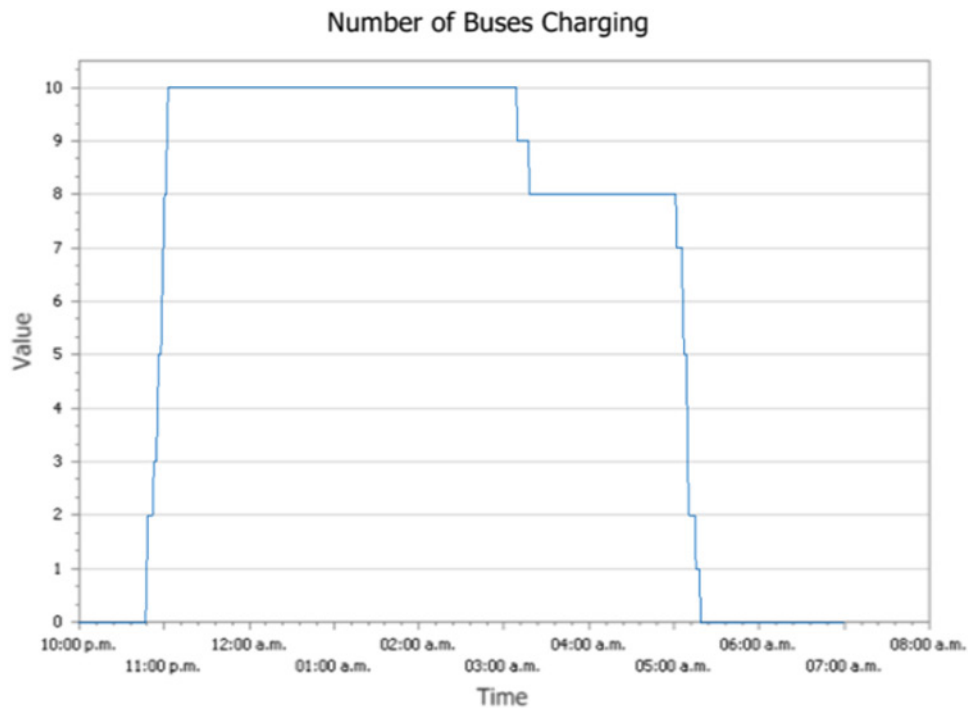
Fig. 11 *Number of buses charging in each time*

the demand of the charging period. Assuming eight chargers and a security factor of 25%, we can say that the capacity of the transformer would be 1 MW to ensure correct operation of the charging service.

In addition, the behaviour of the fleet was modelled in a discrete event simulation environment in order to validate some of the results obtained. In this model, a server with a specific capacity was used to model the charging station. For the simulation a source was used that generated entities (in this case buses) with an exponential distribution for time between arrivals with a mean of 0.7 min, in order to model the arrivals shown in Fig. 8. From all the buses created by the source, only a percentage will be candidates to enter into the charging station, the rest will go directly to the parking area.

On the other side, the distribution used to model the attention time in the server was based in Fig. 9. In this case, the server was set with the capacity to attend ten buses at the same time and a normal distribution with a mean of 125 min and a standard deviation of 6 min. Fig. 11 shows the total number of buses that are served simultaneously during all the recharging service at night.

4 Conclusions

This paper has proposed a general procedure to compute the load demand profile from a parking lot where a fleet of buses with electric propulsion mechanisms are charged. At the same time, this procedure allows the computation of the number of required batteries' chargers to be installed in a charging station placed at a parking lot in order to satisfy and ensure the operation of the fleet.

The proposed procedure is divided into three different stages, the first one models the daily energy utilisation of the batteries based on Monte Carlo simulations and route characteristics. The second one models the process in the charging station based on discrete event simulation of queues of buses served by a lot of available chargers. The third step computes the final demand profile in the parking lot because of the charging process based on the power consumption of batteries' chargers and the utilisation of the available charges.

A sequential simulation was carried out for several days in order to stabilise the computation of the energy consumption for each bus in one day of operation. Additionally, several Monte Carlo

realisations had to be considered in order to have more reliable results because of the statistical randomness of some parameters.

The proposed procedure also allows the computation of the power demand profile and the peak load, and the computation of the general characteristics of electrical infrastructure to supply the power to the station.

6 References

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